SPATIAL SENSOR NETWORK BASED TARGET TRACKING BY CLASSIFICATION

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Electronics and Communication Engineering

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CERTIFICATE

This is to certify that the work done in the thesis entitled **Spatial Sensor network based target tracking by classification** by **Choppa Vivek Krishna** is carried out by him in National Institute of Technology, Rourkela under the supervision and guidance of **Prof. Upendra Kumar Sahoo** during 2014-2015 in partial fulfillment for the award of the degree in Dual Degree in Electronics and Communication Engineering (Communication and Signal Processing), National Institute of Technology, Rourkela.

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DECLARATION

I certify that,

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ABSTRACT

The wide use of sensor networks in the day to day communication in recent trends made tracking a significant feature in monitoring systems. The automated systems capable of detection and tracking of targets is a desirable application in many fields.

Firstly, deploy a sensor network with appropriate space between sensors and then introduce targets into the network. As the sensors detect the targets, each sensor communicates with neighborhood sensor nodes and one of those sensors are elected as cell-head which will calculate the position of target from the data and transmit that to sink. This process is repeated iteratively to track the moving target. Feature extraction methods and classification techniques have been studied to classify targets by their type. For the challenging task of Multi-target tracking, the methods of sequential Bayesian filtering and Sequential Monte Carlo-Particle Hypothesis Density filters are sought.

Accurate algorithms have been simulated for Localization and tracking of target using the data of sensor strengths which are collaboratively communicated among the sensors. Direction of moving target inside a cell was estimated. Algorithm for Hierarchical multi-hop communication model was established.

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Chapter 1

Introduction

1.1 Background and Motivation

In the age of robotic machines, budding towards replacing humans to carry out different tasks, there is a demand for surveillance of objects or targets by machines in different environments. Distributed sensor networks are one such possibility to detect, track and classify different vehicles, moving objects etc. Different sensing modalities such as acoustic, seismic data are detected by sensors to accomplish this task. Due to the availability of modern low cost sensors, large scale sensor networks are being used in applications such as wide area surveillance, disaster response, environmental monitoring, military applications etc.

These can free human beings from time consuming, labor intensive jobs, related to high risks of health and safety. Though radar can monitor across wide area even in dark, it is very highly expensive to implement compared to sensor technology. Traffic managements and intelligent transport systems of automated driver assistance systems are crucial applications of road vehicle recognition. A number of tracking systems have been published and we will be discussing a few of them below.

The instrumentation of a hostile area with conveyed sensors is a thought of decades-old, with executions dating at any rate as long back as the Vietnam-period Igloo White project. Unattended ground sensors (UGS) do exist today that can identify, characterize, and focus the bearing of development of entering faculty and vehicles. The Remotely Monitored and

Battlefield Sensor System (REMBASS) illustrates UGS frameworks being used today [12]. REMBASS abuses distantly checked sensors, hand-deployed along likely for streets of methodology. These sensors react to acoustic-seismic vitality, infrared vitality, and attractive changes to field to recognize foe exercises. REMBASS forms the sensor information mainly and yields recognition what's more, classification data remotely, either straightforwardly or by radio repeaters, to sensor observing set (SMS). Messages are decoded, showed, and recorded to give a period staged record of gatecrasher movement at the SMS. Like REMBASS and Igloo White, a large portion of the current radio-based unsupervised ground sensor frameworks have constrained systems administration capacity and impart their readings of the sensor or interruption discoveries over moderately long and habitually one directional radio connections to a focal checking station, maybe through one or more straightforward repeater stations. Since these frameworks utilize communication of long joins, they use valuable vitality amid transmission, which thusly lessens their overall time. For instance, a REMBASS sensor hub, once deployed, can be unsupervised for just 30 days. Late research has exhibited the practicality of specially appointed elevated organizations of 1 dimensional sensor systems that can recognize and follow vehicles. In March 2001, scientists from the University of California at Berkeley exhibited the arrangement of a sensor system onto a street from an unmanned aerial vehicle (UAV) at Twenty nine Palms, California, at the Marine Corps Air/Ground Combat Center. The system set up a period multi-jump communication system, synchronized among the hubs on the ground, whose employment was to identify and follow vehicles disregarding through the region a soil street. The tracked vehicle data was gathered from the sensors utilizing the UAV as a part of an over move and after the transferred to a spectator at the base

1.2 Thesis Objective

The objective of the thesis is:

a) To design a Target localization algorithm using the detected sensor data and the communication among the neighborhood sensors.

b) To implement single target tracking and model a multi-hop communication system to transmit the data to sink.

c) To study the techniques of multi-target tracking in a distributed sensor network.

1.3 Literature review

A literature survey is conducted to understand the past research trends in Detection, classification and tracking of targets in a distributed sensor network. This survey includes the search of single target tracking algorithms, efficient multi-hop communication models, Localization algorithms, feature extraction methods, classification techniques, multi-target tracking algorithms and efficiencies of different combinations.

Many researches have been done in the field of tracking targets in sensor network. Among them, the paper on "**Detection, classification and tracking of targets in a distributed sensor network**" is reviewed to have knowledge on the algorithm of single target tracking and the idea of energy based collaborative target localization. It provides the knowledge of different classification techniques that can be used for classification purpose of targets. It also compares the efficiency of different classification techniques with results. For feature selection and acoustic classification purpose, the paper “**Distributed and Efficient classifiers for wireless Audio-Sensor Networks**” has been studied. In this paper, representative, yet low-dimensional feature vectors of the acoustic signals are described using power spectral density. Two popular approaches of Data fusion (DAF) and Decision fusion (DEF) are explained in this paper. Formation of clusters on demand, when a signal suggests the presence of a target is detected by a sensors of minimum number is described.

The paper “**Multi-Target tracking in distributed sensor network**” presents the estimation algorithms for target tracking such as sequential Bayesian filter, Kalman filter, Bayesian formulation of Multi-target tracking, Data association possibilities etc. It also provides you with an overview of the traditional approaches of Multi-target tracking such as MHT (Multiple hypothesis tracking), JPDAF (joint probabilistic data association filter), Markov chain Monte carlo methods and the scenario of crossing targets.

The paper “**Multi-EAP: Approximately Optimal Multiple Estimate Extraction for the SMC-PHD Filter**” describes the Multi-estimate extraction (MEE) which is an essential requirement for multi-target tracker. The sequential Monte Carlo implementation of Probability hypothesis density (SMC-PHD) filter has been studied here. The decision and association techniques are employed to distinguish observations of targets from clutter and to associate particles to observations for individual estimate extraction. Here the MEE problem is considered as a family of parallel single estimate extraction problems in which the optimal Expected a Posteriori (EAP) estimator is employed.

The paper "**A security mechanism for clustered wireless sensor networks based on elliptic curve cryptography**" is referred to implement two-tiered clustered wireless sensor network. This network was chosen because of the flexibility to travel in multiple neighborhood paths to reach the sink.

1.4 Thesis Organization

The thesis is organized as follows

Chapter 2 describes different Target localization techniques.

Chapter 3 is focused on target tracking algorithms and multi-hop communication models.

Chapter 4 describes the Target classification techniques and feature selection methods.

Chapter 5 is concentrated on Multi-target tracking techniques in distributed sensor network.

Chapter 6 presents and discusses the results.

Chapter 7 gives the conclusion and the scope of any future work in the field.

Chapter 2

Target Localization

Localization is one of the most important task of the wireless sensor networks (WSNs). There are lots of localization techniques appropriate to different requirements with and without transmitting powers of source node, distance based and angle based localizations etc. Some of these different localization techniques are discussed below.

2.1 Gauss Newton Localization

This is a distance-based localization implemented with the assumption that we are aware of transmitting power of source node. Though this approach is a simple and efficient technique to localize a target, it is not very practical since we do not know the transmitting power of sensor nodes in general. The following is the mathematical model to deduce the location of mobile target by Gauss-Newton method [3].

$$N = 4; m = 1, noisepow = 20; network\ size = 100$$

$$anchorloc = \begin{bmatrix} 0 & 0 \\ 100 & 0 \\ 0 & 100 \\ 100 & 100 \end{bmatrix}$$

$$mobileloc = [a \quad b]$$

$$distance(n)_{n=1}^{4} = \sqrt{((anchorloc(n,1) - a)^2 + (anchorloc(n,2) - b)^2)}$$

$$distancenoisy(n)_{n=1}^{4} = distance(n)_{n=1}^{4}[1 + \frac{20}{100} \times (rand(N,1) - \frac{1}{2})]$$

$$mobilelocest = (x_o, y_o)$$

Iterate :

$$distanceest = \begin{bmatrix} \sqrt(x^2 + y^2) \\ \sqrt((100 - x)^2 + y^2) \\ \sqrt(x^2 + (100 - y)^2) \\ \sqrt((100 - x)^2 + (100 - y)^2) \end{bmatrix}$$

$$f(x,y) = distanceest - distancenoisy$$

$$f'(x,y) = \begin{bmatrix} \frac{x}{\sqrt(x^2 + y^2)} & \frac{y}{\sqrt(x^2 + y^2)} \\ \frac{x - 100}{\sqrt((x - 100)^2 + y^2)} & \frac{y}{\sqrt((x - 100)^2 + y^2)} \\ \frac{x}{\sqrt(x^2 + (y - 100)^2)} & \frac{y - 100}{\sqrt(x^2 + (y - 100)^2)} \\ \frac{x - 100}{\sqrt((x - 100)^2 + (y - 100)^2)} & \frac{y - 100}{\sqrt((x - 100)^2 + (y - 100)^2)} \end{bmatrix}$$

$$A = f'(x_o, y_o); B = f(x_o, y_o)$$

$$\Delta = -((A^t \times A)^{-1} \times A^t) \times B$$

$$mobilelocest = mobilelocest + \Delta'$$

Go to iterate and update mobilelocest and continue this loop until the Δ reaches a very minimum amount. Final mobilelocest will give you a value very closer to the exact position.

2.2 Temporal Ratio-based localization

For this localization, we need to know the initial target position and store the observation sensor data of previous instant. This is the only drawback of this localization technique. In this technique, we take the ratio of received signal strengths of a sensor node at two consecutive time instants which are inversely proportional to the square of their distance to the source node. Since, we already know the location of source node in the previous time instant, we get a circle equation as a solution for one sensor node. Similarly, we can get three more circle equations in that cell and these circles will give the target location as we solve them.

Let (x_1, y_1) be the target location at time t.

$$r_t = \sqrt{}((a - x_1)^2 + (b - y_1)^2$$

Where (a, b) is the sensor location.

$$\frac{p_t}{p_{t+1}} = \frac{r_{t+1}^2}{r_t^2}$$

$$(x - a)^2 + (y - b)^2 = r_{t+1}^2$$

Where (x, y) is the target location, similarly we can derive another few circle equations with centers as their corresponding sensor locations. By solving these circles, we get the exact location of the target.

2.3 Target localization without transmitting power

In this method, we take the ratios of received powers of any two sensor nodes inside a cell to cancel out the transmitted power of source node from the equations [9]. As we solve these different ratios, we get different circles with their centers and radii as given below. On solving these radii, we get the appropriate location of source node [1].

Let P_1, P_2, P_3, P_4 be the received powers at sensor locations of four different corners with their locations given as $(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)$.

$$k_{ij} = \frac{p_i}{p_j}$$

$$Cx_{ij} = \frac{x_j - k_{ij} \times x_i}{1 - k_{ij}} \qquad , \qquad Cy_{ij} = \frac{y_j - k_{ij} \times y_i}{1 - k_{ij}}$$

$$r_{ij}^2 = \frac{(x_j - k_{ij} \times x\_i)}{\left(1 - k_{ij}\right)^2} - \frac{(x_j^2 - k_{ij} \times x_i^2)}{1 - k_{ij}} + \frac{(y_j - k_{ij} \times y_i)}{\left(1 - k_{ij}\right)^2} - \frac{(y_j^2 - k_{ij} \times y_i^2)}{1 - k_{ij}}$$

Cx_{ij}, Cy_{ij} and r_{ij}^2 gives circle for ratio $\frac{P_i}{P_j}$. By solving different circles resulting from different possible ratios, we can derive the target location.

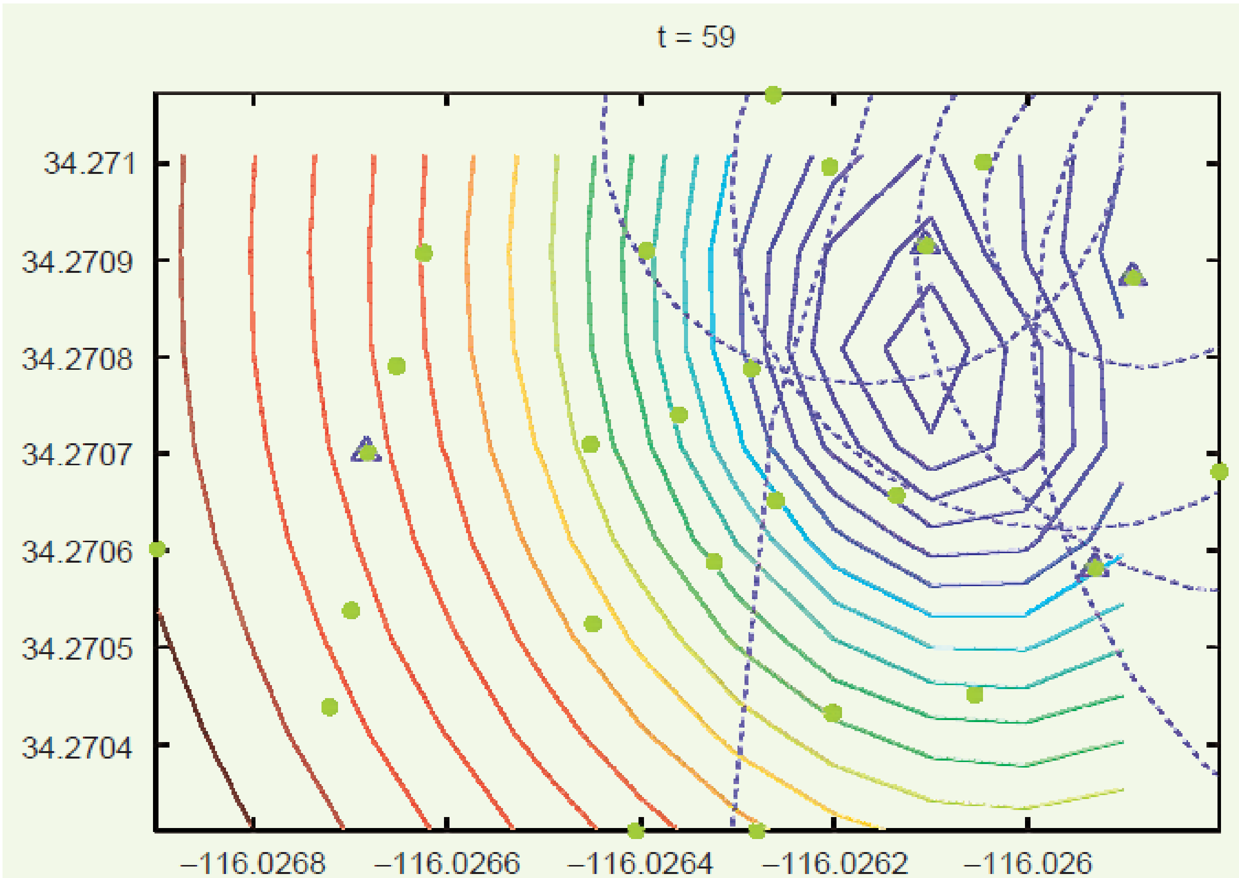

Figure 1: Source Localization using CSP of sensor nodes

Chapter 3

Target tracking and MHC

3.1 Tracking of single Target

The below figure outlines the essential thought of area based CSP for the recognition and following of a solitary target [1]. Under the supposition that a potential target may enter the checked region through one of the four corners, four sensor cells, A, B, C and D. Nodes in each of four cells are enacted to distinguish potential targets. Every initiated node runs an energy recognition calculation whose yield is examined at the earlier settled rate depending on the attributes of expected targets. Assume a target enters Cell A. Following of the target comprises of the accompanying five stages:

a) Some and maybe the greater part of the nodes in Cell A distinguish the target. These nodes are the dynamic nodes, Cell A is the dynamic cell. The dynamic nodes additionally yield CPA of time data. The dynamic nodes accounts their energy indicator yields to the administrator nodes at N progressive time moments.

b) At every time moment, the administrator nodes focus the area of the focus from the energy indicator yields of the dynamic nodes. The easiest assessment of target area at a moment is the area of the node with strongest sign right then and there. Be that as it may, more advanced calculations for target confinement may be utilized. Such confinement calculations legitimize their higher many-sided quality just if the precision of their area determination is better than the node dispersing.

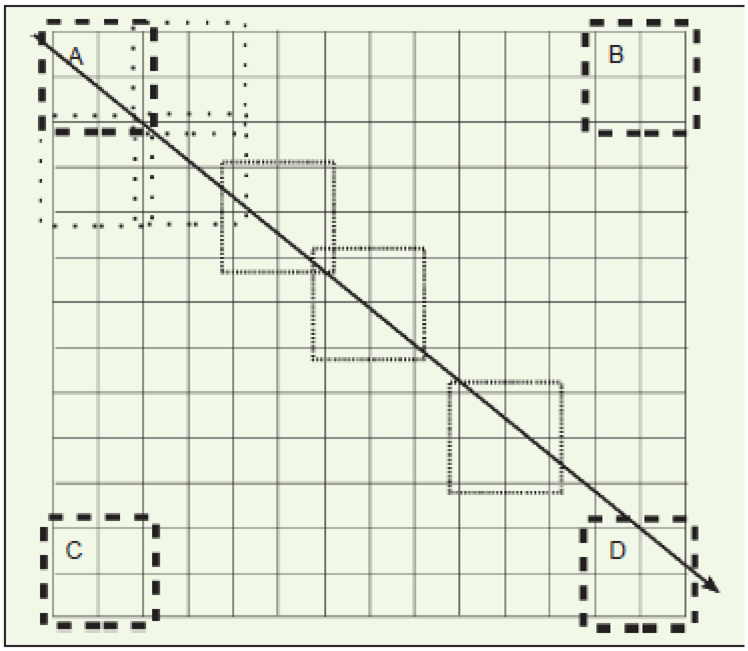

Figure 2: A schematic illustrating detection and tracking of a single target

c) The chief nodes use areas of the focus at the N progressive time moments to foresee the area of the focus at M (< N) number of future time moments.

d) The anticipated positions of target are utilized to make new cells that a target is prone to enter. This is outlined in Fig where the three spotted cells speak to the districts that the target is more likely to enter after the present dynamic (Cell A in Fig). A subset of all these cells is enacted for ensuing recognition and following of the target.

e) Once a target is distinguished in one of the new cells, then it is assigned as the new dynamic cell and as the nodes in the unique dynamic (Cell A in Fig) may be placed in the standby state to save energy.

Steps (a-e) are rehashed for new dynamic cell, and this frames the premise of distinguishing and following a solitary target. For every distinguished focus on, a data field containing following data, for example, the area of the focus at sure past times, is normally gone from one dynamic cell to the following one. This is especially critical on account of various targets. Comparative calculations are being produced by different gatherings also [1].

3.2 Target tracking by Estimation Algorithms

Sequential Bayesian filtering:

Let x^t be the target state at time t which is to be estimated from measurement history of $\bar{z}^t$, where

$$\bar{z}^t = \{z^0, z^1, \dots, z^t\}$$

are collection of the measurements from initial time to time t.

Target dynamics $p(x^t/x^{t-1})$ are characterized by a stationary Markov model. The probability distribution $p(z^t/x^t)$ is an observation model which relates target state x^t to sensor management z^t and it is conditionally independent. Under these assumptions, tracking is a sequential Bayesian filtering [5].

$$p\left(\frac{x^t}{\bar{z}^t}\right) \propto p(z^t) \times \int_X p\left(\frac{x^t}{x^{t-1}}\right) \times p\left(\frac{x^{t-1}}{\bar{z}^{t-1}}\right) dx^{t-1}$$

In prediction step, from the target belief at t-1, the distribution of likely states at time t are computed. Contribution of likelihood z^t is included by multiplication of likelihood function. Since, the distribution current filter $p(x^t/z^t)$ is computed from the distribution of previous filter $p(x^t/\bar{z}^{t-1})$ and the new observation z^t, this filter equation is recursive in nature. Under the assumption that observation model and object dynamics are both linear in x^t and the uncertainty in both models are Gaussian, the sequential Bayesian filter is a Kalman filter. The posterior belief of $p(x^t/\bar{z}^t)$ is also Gaussian. Since, covariance and mean characterizes some Gaussians, the kalman filter equation update the average $\bar{x} \triangleq E[x^t/\bar{z}^t]$ and the covariance $P \triangleq E[(x^t - \bar{x})(x^t - \bar{x})']$ measurements are observed recursively.

Particle filter is another alternative for this application. It is a non-parametric monte carlo based sampling method, representing a probability distribution as a set of point samples weighted. $\{x_i, w_i\}_{i=1}^n$, referred to as a particle set. The particle filter algorithm updates the sample points $\{x_i\}$ and their weights $\{w_i\}$ based on the target dynamics $p(x^t/x^{t-1})$ and the observation likelihood model which is (z^t/x^t) . The non-linear dynamics and multi-modal observation models can be accommodated in this filter but at the cost of more storage requirements and computation [5].

3.2 Multi-Hop Communication

In a distributed sensor network, communication, computation, power and sensing are four crucial constraints. Let us take a typical sensor network of large number of battery powered tiny nodes of sensors with an inexpensive CPU and wireless antenna, mixed with a smaller number of high end sensors. The operational capabilities of those sensors for prolonging periods of time is a desirable characteristic. Communication requirements of the network should not exceed its potential for any application. The computational capabilities of inexpensive sensor nodes are often poor. Hence, developers must write algorithms of less complexity which can take advantage of distributed computational resources of the sensor network that can even sacrifice the quality of sensing, if necessary.

3.2.1 Hierarchical multi hop communication model

In this model, we deploy a two tier sensor network with large number of inexpensive sensor nodes and few high-end sensors called cell-heads. All the nodes can receive and transmit signals from adjacent nodes which are within the range of that node as long as they are in active mode. In the same way, cell-heads can communicate with adjacent cell-heads and nodes except that cell-heads have larger range compared to sensor nodes [16].

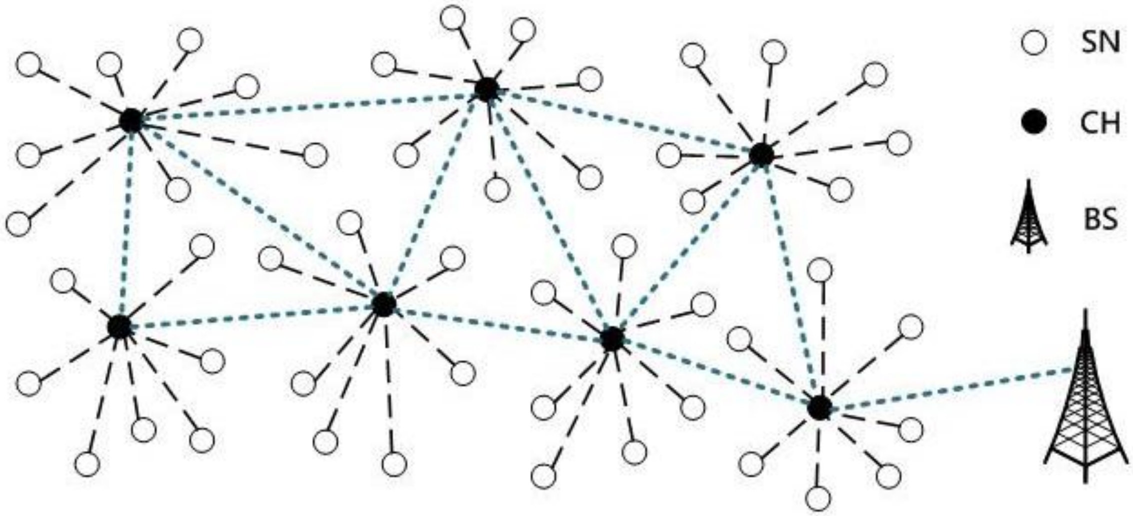

Figure 3: A schematic illustrating the two-tier clustered sensor network

In this algorithm, before deploying sensor nodes in the area of interest, we store the value of threshold and initial power flags fl(t) and fl(t+1) appropriately. Load the location of neighborhood cell-head which is towards sink in every cell-head. Below steps are followed to each iteration.

a) Send all sensor values and their locations to their respective cell heads.

b) Check if greater than four sensors of that cell have greater than threshold value of sensor signal strength. If yes

c) Take out top four sensor values and their locations.

d) Using any localization technique, localize the target location.

e) Send flag 1 to all the neighborhood cell-heads and they update that to fl(t+1) of their sensor nodes for next iteration.

f) Check location of neighborhood cell-head towards sink and transmit the localized target point data to that cell-head and that will again send it next one until the sink.

g) Shift the flag data fl(t+1) to fl(t) and set fl(t+1) to zero and repeat the steps (a-g) for next iteration.

3.2.2 Direction measurement for power conservation

Consider the movement of target from one place to another inside a cell of four nodes. Let $d(n,t)$ be the signal strength of node n at time instant t. Then

$$D(n) = d(n,1) - d(n,2)$$

Where $D(n)$ is the difference in signal strengths at two time instants of node n. The rest of the algorithm written below to determine the direction of moving target inside a cell.

```
s=sort(Difference);

    for i=4:-1:3

            if s(i)==D(1)     angular spectrum of node at left-bottom
                ang(k)=135;
                k=k+1;
                ang(k)=315;
                k=k+1;
            elseif s(i)==D(2) angular spectrum of node at right bottom
                ang(k)=225;
                k=k+1;
                ang(k)=405;
```

```
            k=k+1;
        elseif s(i)==D(3) angular spectrum of node at left-bottom
            ang(k)=45;
            k=k+1;
            ang(k)=225;
            k=k+1;
        elseif s(i)==D(4) angular spectrum of node at left-bottom
            ang(k)=315;
            k=k+1;
            ang(k)=495;
            k=k+1;
        end
end

a=sort(ang);

if (a(4)-a(1))>360
    b=[a(1) a(4)];
else
    b=[a(2) a(3)];
end

if b(1)>360
    b(1)=b(1)-360;
end
if b(2)>360
    b(2)=b(2)-360;
end
```

```
b
```

The array b will give the output as an angular spectrum of 90 degrees as the direction in which target is moving. From this data we can set all the sensors in that direction to active mode for next iteration or time instant and rest of them in sleep mode.

Chapter 4

Target classification

4.1 Feature Selection

4.1.1 Power spectral density

A vehicle sound is generally a stochastic signal, but it can be considered as a stationary signal for short period of time. Here 256 data points are sampled at a frequency of 4.96 KHz over the signal duration of 51.2 ms. A linear vector of resolution 38.75 hz and 128 PSD points is yielded from the PSD estimates of 256 data points. Though we consider all the 128 dimensions at the beginning, we subsequently prune many of them. The frequencies corresponding to maximum power are considered and the rest of the dimensions were neglected. All the dimensions corresponding to maximum frequency bands which are reported from different samples of a particular class were stored in a single set. Based on the repetitions of a particular frequency band in that set, we allot rankings to those dimensions. Then, those dimensions are sorted according to their rankings. We further prune some more frequency bands by selecting a percentage of total bands. These bands constitute a set which characterizes a particular class and this process is repeated for all the classes [2].

In Independent feature selection (IFS) scheme, we create feature vectors by combining all the sets corresponding to all the classes. In Global feature selection (GFS) scheme, we create feature vectors by taking intersection of all the frequency bands corresponding to all the classes. The problem with GFS scheme is that sometimes we may end up with an empty feature vector. In those cases, we combine all the first frequency bands of all the sets corresponding all the different classes to create feature vectors [2].

Before the deployment of sensors, these feature vectors are uploaded into them. Now the sensors can extract PSD points of unknown vehicles, from their sampled acoustic signal, and can directly fetch IFS/GFS feature vectors of unknown sample using the selected dimensions learned from the training phase.

4.2 Classifiers

4.2.1 k-nearest neighbor classifier

In KNN classifier, all the training features are used as a set of prototypes. During the testing phase, the distance between all the prototypes and the test vector are calculated. The class of test vector is determined by the majority number of classes in the k-nearest neighbor prototypes. If k=1, then it is called nearest neighbor classifier. Since it requires too much memory storage and processing power for testing, this is not suitable for practical applications.

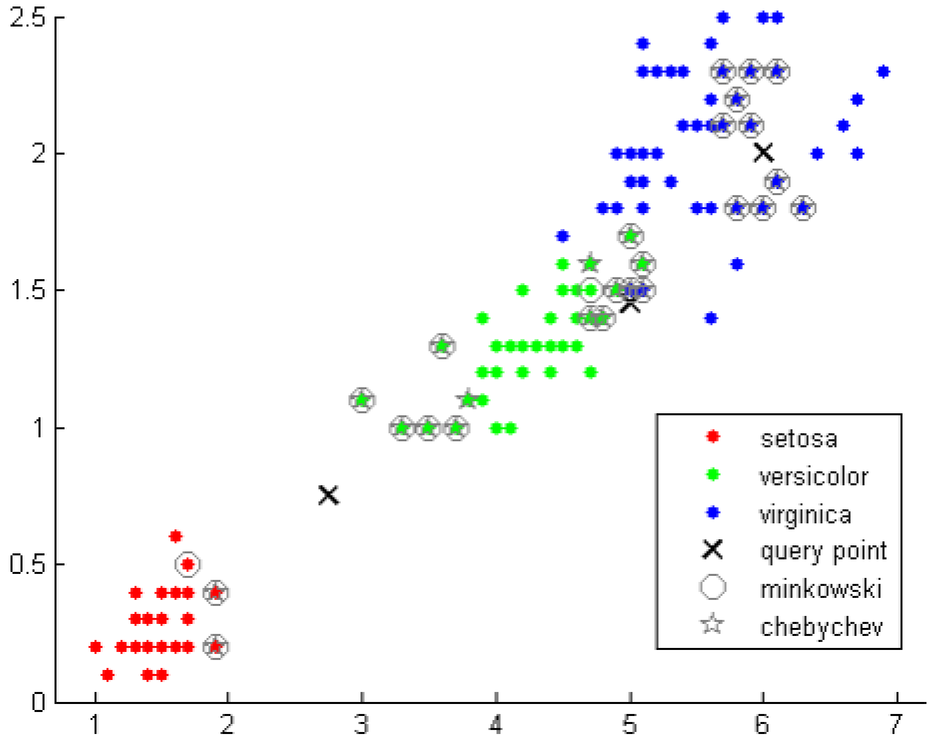

Figure 4: Illustration of KNN classifier

4.2.2 Maximum Likelihood classifier

In case of Gaussian mixture density model, the distribution of training vectors belonging to same class are modeled as a mixture of Gaussian density functions. The likelihood function is

$$p\left(\frac{x}{\omega_i}\right) = G\left(\frac{x}{\theta_i}\right) = \sum_k \alpha_{ik}|\delta_{ik}|^{-\frac{N}{2}}\exp(-\frac{1}{2}(x - m_{ik})^T\delta_{ik}^{-1}(x - m_{ik}))$$

Where $\theta_t = [\alpha_{i1}, \dots, \alpha_{ip}, m_{i1}, \dots, m_{ip}, \delta_{i1}, \dots, \delta_{ip}]$ are the mixture, mean, covariance parameters of the P mixture densities corresponding to class ω_t.By applying appropriate clustering algorithms like the expectation-maximization algorithm or k-means algorithm, to the each class training vectors, these can be identified as model parameters. Here $g_i(x) = G_i(x/\theta_i)p(\omega_i)$ is the discriminant function where the prior probability $p(\omega_i)$ by the relative number of training vectors are approximated in each class i.

4.2.3 Support Vector Machine (SVM)

It is a supervised learning classifier to identify "the hyper plane for which the margin of separation is maximized". The assumptions of standard two-class linear classification algorithm is

(a) Samples from two classes in their feature space are linearly separable.

(b) There exists a hyper plane that maximizes the margin, or the sum of shortest distances between each sample point in each class and a linear line that separates two classes.

By using the method called "kernel mapping" [1] , SVM can perform classification of non-linearly separable samples. This technique maps the feature vectors in the feature space into a higher dimension space, where the samples can be linearly separable.

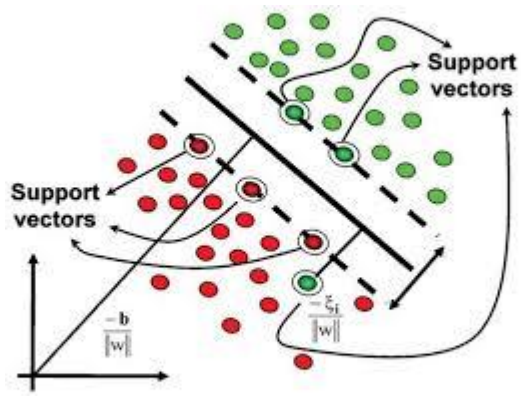

Figure 5: Illustration of Support Vector Machine

Let $\varphi_i(x)_{i=1}^{M}$ be a set of non-linear transformations mapped to an M-dimensional feature space (M>N) from the N-dimensional input vector into. The weights $\{w_1, w_2, .., w_m\}$ characterizing a linear classifier operates in the higher dimensional feature space [2].

$$g(x) = \sum_{j=1}^{m} w_j \times \varphi_j(x) + b$$

Where b is the bias parameter of the classifier.

$$w_j = \sum_{i=1}^{Q} \alpha_i \times \varphi_j(x_i) \ , j = 1,2, .. M$$

$$g(x) = \sum_{i=1}^{Q} \alpha_i \times k(x, x_i) + b$$

Where

$$k(x, x_i) = \sum_{j=1}^{M} \varphi_j(x) \times \varphi_j(x_i)$$

is the symmetrical kernel representing SVM.

Third degree polynomial kernel: $k(x, x_i) = (x' \times x_i + 1)^3$

However, high amounts of time and memory consuming is a disadvantage of SVM. Other applications where SVM is widely applied are classification of indoor acoustic event and automated acoustic wood condition monitoring in the transportation industry [15].

Chapter 5

Multi target tracking

Brief introduction into the approach of higher order voronoi diagram:

The goal is to situate a non-uniform scope inside of the checked zone to permit recognizing the target(s) by various sensor nodes [13]. We indicate how the proposed calculation adjusts to the circumstance where numerous targets will move in the checked zone. In addition, we acquaint a calculation with find excess nodes (which don't give extra data about target position). This calculation is indicated to be viable in diminishing the energy utilization utilizing an action planning approach.

5.1 Multiple Hypothesis tracking (MHT) and JPDAF

The thought is to comprehensively list the set of all associations recursively, called hypothesis, of estimations to existing tracks, false alerts and new tracks while regarding the common avoidance association limitation. Preference of this methodology is that the number of tracks need not be known from the earlier on the grounds that track starts and terminations are expressly guessed. Moreover, information association choices are successfully postponed until more information is gotten since various hypothesis are kept. In this way, MHT addresses low identification likelihood, high false alert rates, start and end of tracks, and deferred estimations.

Then again, this methodology experiences substantial storage room necessities and exponentially expanding preparing, so a key piece of making this approach useful is to prune terrible hypotheses or consolidate comparable hypotheses [5].

The Joint probabilistic data association filter (JPDAF) methodology is to upgrade every individual track state with weighted mixes of all estimations. Along these lines, the key piece of this methodology is figuring the likelihood that estimations can be connected with tracks so that the common avoidance limitation is regarded. A detriment of this methodology is that the number of targets needs to be known from the earlier.

The relationship in the middle of MHT and JPDAF has been underemphasized in the writing. JPDAF is a specific method for consolidating the various theories created by MHT into a solitary speculation at every time step and, consequently, can be seen as an occasion of MHT. We will expound on this relationship now on the grounds that all methodologies to information affiliation can be seen as occasions of MHT, and the thought of consolidating theories is the reasonable establishment behind new asset mindful representations to be talked about in the accompanying segment.

Consider the target cases, where track B and A are freely dispersed by $p_A^{t-1}(x)$ and $p_B^{t-1}(x)$, separately. There are two estimations seen at time t given by z_1^t and z_2^t. Expecting that there are no false alerts or missed estimations for the purpose to simplify the discussion, there are two speculations created by MHT.

$$H_0 = track\ a\ associated\ with\ z_1^t\ and\ track\ b\ associates\ with\ z_2^t.$$

$$H_1 = track\ b\ associated\ with\ z_1^t\ and\ track\ a\ associates\ with\ z_2^t.$$

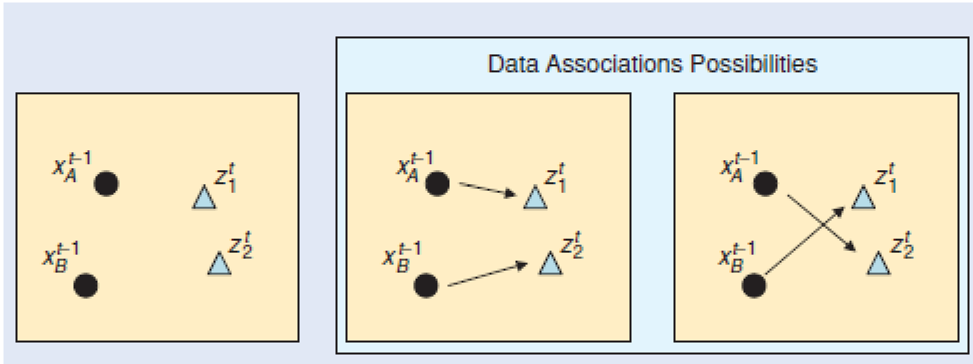

Figure 6: Data association example. (a) Two target (circles) with two measurements (triangles)

Before predicting association probabilities, Each track's belief is predicted and forwarded to the current time.

$$p_j^t(x) = \int p\left(\frac{x^t}{x^{t-1}}\right) p_j^{t-1}(x^{t-1}) dx^{t-1}$$

For $j \in \{A, B\}$.

$$\gamma_0 = \int p\left(\frac{z_1^t}{x_A}\right). P\left(\frac{z_2^t}{x_B}\right). p_A^t(x_A). p_B^t(x_B) dx_A dx_B$$

$$\gamma_1 = \int p\left(\frac{z_2^t}{x_A}\right). p\left(\frac{z_1^t}{x_B}\right). p_A^t(x_A). p_B^t(x_B) dx_A dx_B$$

The association probabilities are

$$p(H_0) = \gamma_0/(\gamma_0 + \gamma_1)$$

$$p(H_1) = \gamma_1/(\gamma_0 + \gamma_1)$$

$$p_A^t\left(\frac{x}{H_0}\right) = \alpha_0. p\left(\frac{z_1^t}{x}\right). p_A^t(x)$$

$$p_A^t\left(\frac{x}{H_1}\right) = \alpha_1 . p\left(\frac{z_2^t}{x}\right) . p_A^t(x)$$

JPDAF combines these multiple hypotheses by

$$p_{JPDAF,j}^t(x) = p_j^t\left(\frac{x}{H_0}\right) . p(H_0) + p_j^t\left(\frac{x}{H_1}\right) . p(H_1)$$

For each track $j \in \{A, B\}$.

This soft data association approach of JPDAF is the marginalization of track.

5.2 MEAP ESTIMATOR FOR MEE

5.2.1 SMC IMPLEMENTATION OF PHD FILTER AND MEE

The random finite set (RFS) hypothesis gives a flawless apparatus to speak to the obscure and size-fluctuating state set and perception set included in the MTT scene. Let $F(x)$ characterize the space of limited subsets of targets $X \subseteq R^{nx}$ and $F(z)$ characterize the space of limited subsets of perceptions $Z \subseteq R^{nz}$. Assume that at time k, the accumulations of the conditions of targets are a RFS $x_k = \{x_{k,1}, \dots., x_{k,N_k}\} \in F(x)$ where N_k is the quantity of targets, and the perceptions accessible (that comprises of the genuine perceptions from targets and disorder) are a RFS $z_k = \{z_{k,1}, \dots, z_{k,m_k}\} \in F(z)$ where m_k is the quantity of perceptions [7].

One of the attractive feature of SMC-PHD filter is, its complexity is independent of (time-varying) number of targets [14].

Given a multi-target state X_{k-1} at time k-1, each $x_{k-1} \in X_{k-1}$ either keeps on existing at time k with the survival likelihood $p_{s,k}(x_{k-1})$ and move to another state with a transition likelihood density $f_{\frac{k}{k-1}}(x_k/x_{k-1})$ or vanish with likelihood $1 - p_{(s,k)}(x_{k-1})$. At time k , a given target $x_k \in X_k$ is either recognized with identification likelihood $p_{D,k}(x_k)$ and produces a perception $z_k \in Z_k$

With likelihood $g_k(z_k/x_k)$ or miss-detected with probability $1 - p_{D,k}(x_k)$.

Assumptions of standard PHD filter:

(A.1) Each target advances and produces observations autonomously of others;

(A.2) The disarray dispersion is Poisson and autonomous of the observations;

(A.3) One target can create close to one observation at every output;

(A.4) the showing up target procedure is Poisson.

Let $D_{\frac{k}{k}}$ and $D_{\frac{k}{k-1}}$ be the PHD related to the multi-target posterior and prior thickness, namely

$$D_{\frac{k}{k}} = D_{\frac{k}{k}}(x_k/Z_{1:k}), \qquad D_{\frac{k}{k-1}} = D_{\frac{k}{k-1}}(x_k/z_{1:(k-1)}) \ .$$

The PHD channel develops after some time through the taking after Bayes recursions which comprises of two sorts of overhauling steps [7]:

1) time-upgrade step (PHD indicator)

$$D_{\frac{k}{k-1}} = \int \phi_{\frac{k}{k-1}}\left(\frac{x}{u}\right) D_{\frac{k-1}{k-1}}(u)du + \gamma_k(x)$$

where the accompanying shortened form is utilized

$$\phi_{\frac{k}{k-1}}\left(\frac{x}{u}\right) = p_{s,k}(u) f_{\frac{k}{k-1}}\left(\frac{x}{u}\right) + b_k(x/u)$$

Where $b_k(x/u)$ means the force capacity of the RFS of targets generated from the past state u, and $\gamma_k(x)$ is the conception force capacity of new targets at sweep k.

2) Information upgrade step (PHD updater)

$$D_{\frac{k}{k}}(x) = \left[\left(1 - p_{D,k}(x)\right) + \sum_{z \in Z_k} \frac{p_{D,k}(x) g_k\left(\frac{z}{x}\right)}{k_k(z) + C_k(z)}\right] D_{\frac{k}{k-1}}(x)$$

where $k_k(z)$ is the disorder power at time k and

$$C_k(z) = \int P_{D,k}(u) g_k\left(\frac{z}{u}\right) D_{\frac{k}{k-1}}(u)du$$

The PHD channel has roused an assortment of new deductions, translations and executions. Specifically, the SMC execution of the PHD channel when all is said in done nonlinear state-space models where the commotions can be non-Gaussian has pulled in wide hobbies, counting progressed PF usage, for example, assistant PF, Gaussian entirety PF, Rao-Blackwellised PF furthermore, box-PF. Late improvements incorporate broadened/gathering target following, multi-displaying following, multi-sensor following and the augmentation to higher request, further principled rough guesses. In this paper, we examine the essential form of the SMC-PHD channel for clarity be that as it may, our MEE methodology is normally pertinent to cutting edge.

The SMC implementation of PHD filter:

Given the significance densities $p_k(./z_k)$, proposition densities $q_k(./(x_{k-1}, Z_k))$ and assuming that there are L_{k-1} particles at time k-1 and that j_k new particles are allotted for conceivable new targets at time k, the particle estimate of the indicator $D_{\frac{k}{k-1}}$ can be composed as

$$D_{\frac{k}{k-1}}(x_k) = \sum_{i=1}^{L_{k-1}+j_k} w^i_{\frac{k}{k-1}} \delta_{x_k^i}(x_k)$$

where $\delta_x(.)$ denotes the delta-Dirac mass situated in x, the anticipated state and weight are given individually as

$$x_k^i \sim \begin{cases} q_k\left(\frac{\cdot}{x_{k-1}^i}, Z_k\right), & i = 1, \dots, L_{k-1} \\ p_k\left(\frac{\cdot}{Z_k}\right), & i = L_{k-1}+1, \dots, L_{k-1}+j_k \end{cases}$$

$$w^i_{\frac{k}{k-1}} = \begin{cases} \dfrac{\left(\phi_{\frac{k}{k-1}}\left(\frac{x_k^i}{x_{k-1}^i}\right) w_{k-1}^i\right)}{q_k\left(\frac{x_k^i}{x_{k-1}^i}, Z_k\right)}, i = 1, \dots, L_{k-1} \\ \dfrac{\delta_k(x_k^i)}{j_k p_k\left(\frac{x_k^i}{Z_k}\right)}, & i = L_{k-1}+1, \dots, L_{k+1}+j_k \end{cases}$$

The particle approximation of the PHD updater $D_{\frac{k}{k}}$ is

$$D_{\frac{k}{k}}(x_k) = \sum_{i=1}^{L_{k-1}+j_k} w^i_{\frac{k}{k}} \delta_{x_k^i}(x_k)$$

Where

$$w_{\frac{k}{k}}^{i} = \left[1 - p_{D,k}(x_k^i) + \sum_{z \in Z_k} \frac{p_{D,k}(x_k^i) g_k\left(\frac{z}{x_k^i}\right)}{K_k(z) + C_k(z)}\right] w^{i}{}_{\frac{k}{k-1}}$$

$$C_k(z) = \sum_{j=1}^{L_{k-1}+j_k} c_k^j(z)$$

$$c_k^j(z) = p_{D,k}(x_k^j) g_k\left(\frac{z}{x_k^j}\right) w^{i}{}_{\frac{k}{k-1}}$$

Since the mass of the intensity gives the normal number of targets, the basic way to deal with evaluation the number of targets N_k is adjusting the aggregate weight mass as

$$N_k = \sum_{i=1}^{L_{k-1}+j_k} w_{\frac{k}{k}}^{i}$$

Weight Component of particles:

$$w_k^i(z) = \begin{cases} \left(1 - p_{D,k}(x_k^i)\right) w^{i}{}_{\frac{k}{k-1}}, & if\ z = z_0 \\ \frac{P_{D,k}(x_k^i) g_k\left(\frac{z}{x_k^i}\right)}{K_{k(z)} + C_k(z)} w^{i}{}_{\frac{k}{k-1}}, & if\ z \in Z_k \end{cases}$$

Integrated weight of one particle is

$$\mathrm{w}_{\frac{\mathrm{k}}{\mathrm{k}}}^{\mathrm{i}} = \sum_{z \in \{z_0, Z_k\}} w_k^i(z)$$

The sum of the weight components over all particle corresponding to single observation is

$$W_k(z) = \sum_{i=1}^{L_{k-1}+j_k} w_k^i(z), \qquad z \in \{z_0, Z_k\}$$

Weight component based MEE:

Keeping in mind the end goal to acquire numerous assessments from the joint PHD, disintegration can be done on particles or on the weight of particles. Dissimilar to the molecule bunching that is taking into account the coordinated weight of particles, two MEE techniques that are taking into account weight deterioration have been proposed by Ristic [18] and Zhao [17] for quick reckoning. In them, the weights of particles are deteriorated concerning observations and afterward the weight parts are utilized to compute gauges, which require no grouping of particles. Zhao [17] chooses N_k different observation z from $\{z_0, z_k\}$with the biggest $w_k(z)$ (as called Largest N administer) and for each z, one state-assessment is acquired as the mean of the conditions of all segment weighted particles

$$x_k^{Zhao}(z) = \frac{\sum_{i=1}^{L_{k-1}+j_k} w_k^i(z) x_k^i}{W_k(z)}$$

Interestingly, Ristic [18] decides to concentrate gauges from $z \in \{z_0, z_k\}$ if the commitment W_k^z is greater than a threshold W_t(as called Threshold guideline). This technique has abstained from evaluating the cardinality N_k by total weight mass equation yet an ad-hoc limit must be indicated. The state-gauge comparing to the chose z is given as

$$x_k^{Ristic}(z) = \sum_{i=1}^{L_{k-1}+j_k} w_k^i(z) x_k^i$$

To note, the weight is not standardized which is the main contrast to (14). This disappointment of standardization (as $W_k^i(z)$ is not precisely one) is rectified, which does not utilize the new-conceived particles for estimation extraction. The assessment is computed as takes after

$$x_k^{schikora}(z) = \frac{\sum_{i=1}^{L_{k-1}} w_k^i(z) x_k^i}{\sum_{i=1}^{L_{k-1}} w_k^i(z)}$$

Moreover, this won't report any evaluation for the miss-distinguished target; the same as our methodology. On the other hand, there are still much space to further decrease the connection between evaluations.

This gathering of arrangements utilize the weight parts to ascertain every evaluation, which is inside diverse to the bunching strategy that concentrates every appraisal in view of just a bunch of particles (while utilize the incorporated weight). They isolate the PHD in two unique conduct for the comparative MEE objective. The previous partitions the weight (into segments) however not the particles while the last isolates the particles (by bunching) yet not the weight.

5.2.2 MEAP estimator

NNN-PARTICLE TO OBSERVATION ASSOCIATION:

At the first level, we receive the known closest neighbor association system to separation the particles as to their space vicinity to individual observations. Each particle is related to its closest observation. To note, alerts ought to be paid to the NN part of particles when two or more observations are close. For this situation, the particles are exceedingly blended and the NN association is not so much compelling to manage the relationship. Case in point in figure, two observations (in shading of beat up) are verging on covered (the targets are additionally close), then every observation will be related with just a half number of the particles in the joint cloud (green and red) by utilizing the NN association; the assessments given by every a large portion of the particle cloud is liable to be floated away from the inside as they exclude the particles on the other side in their estimation even the particles are near to them. The same thing can happen for the situation at the point when more observations are near to one another, which is a specific test for the SMC-PHD channel [7].

Making into note of this particular case, we amplify the NN system to incorporate the exact close particles even they are not related to the basic observation agreeing to the NN guideline, in particular the NNN association, as takes after

$$u(z) = N(z) \cup Gate(z)$$

where N(z) is the RFS of the related particles whose closest observation is z and Gate(z) is the RFS of particles that lie in the a predefined entryway scope around observation z (as indicated by the red and green circles of Figure). The entryway needs to be appropriately composed as per the observation commotion. For our situation we propose an extent of 0.5~2-time standard deviation of the observation commotion, which is a level to catch the most huge observations while abstain from overshooting. As a result, the particles in the red/green circle will be related to the green/red observations and will be taken into record exclusively in their appraisal computation. This can be depicted as Algorithm 1, where dis(z,i) is the Euler separation between observation z and the position of particle i in the observation space, $i \to u(z)$ means particle I is added into the RFS u(z).

Algorithm 1 NNN particle to observation association

For $i = 1, \dots, L_{k-1} + j_k$ DO

$$\forall \left\{ z \in Z \middle| z = \max_z g_k\left(z \middle| x_k^i\right) \; or \; dis(z,i) \leq gate \right\}:$$

$$i \to u(z)$$

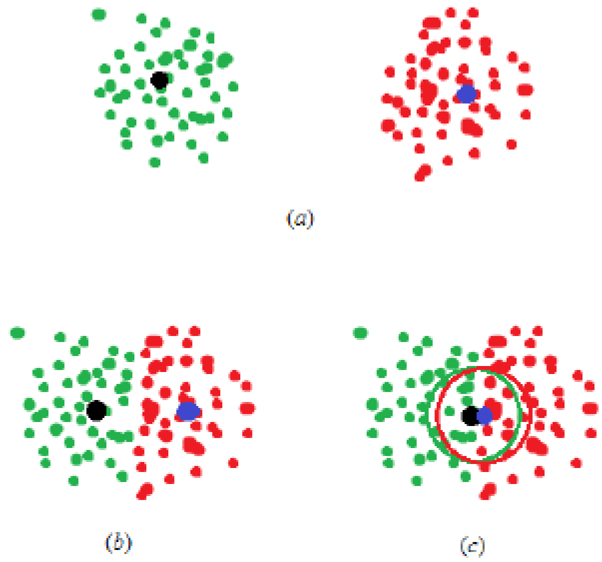

Figure 7: Different space proximities of observations

DISTINGUISH OBSERVATION OF TARGETS FROM CLUTTER:

We propose to partition the aggregate observation RFS Z_k into two RFSs: target-observation RFS $Z_{k,T}$ and mess RFS $Z_{k,c}$, satisfying $Z_k = Z_{k,t} \cup Z_{k,c}$. To execute MEE, the MEAP estimator just employ $Z_{k,t}$. As expected, the condition of targets includes in a Markov procedure while the mess generator does not so much develop with the PHD engendering after some time. This could be utilized to recognize the observations of targets from mess: the target is equivalently more prone to fall in the range of high PHD where the mass of particles is moderately substantial and along these lines the observation of a target will contribute all the more fundamentally to the PHD, i.e. Rule 1. The observations that contribute more fundamentally to the PHD, as far as a larger $W_k(z)$, are more probable produced by the targets. This rule is close to a guideline of the thumb which has really been utilized in existing MEE systems, e.g. Ristic's Threshold control, Zhao's Largest N guideline and the observation-based grouping [17]. In our methodology, we can utilize either the Threshold standard or the Largest N principle to separation observations to obtain $Z_{k,t}$. They compare to the primary stride of Algorithm 2 and 3 individually as named MEAP I and MEAP II. In particular, it is anything but difficult to know, maximally $|Z_k|$ assessments can be separated in both calculations where $|Z_k|$is the cardinality of Z_k.

It is important that Rule 1 is prohibitive as mess generators may fall near to existing particles accordingly giving critical ascent to the PHD and will be taken as a target. For this situation, even the PHD itself will be by regional standards over-assessed and the MEE can't be any better. This is a natural disadvantage of the multi-target thickness channel that is in view of observations of single-edge just. Now that its out in the open, all MEE strategies include some level of choice that is dependably of danger taking. However, we repeat that MEE is an autonomous choice procedure to the channel that won't influence the separating result.

EAP estimator:

For every sub-issue of single observation and an arrangement of particles, the EAP estimator is given as

$$x_k^{EAP(z)} = \sum_{i \in u(z)} x_k^i w_z^i$$

Where the single observation weight w_z^i is updated by the likelihood of observation $z \in Z_{k,T}$ as

$$w_z^i = g_k(z|x_k^i) * w_{k|k-1}^i, \ \sum_{i \in u(z)} w_z^i = 1 \, , \ z \in Z_{k,T}$$

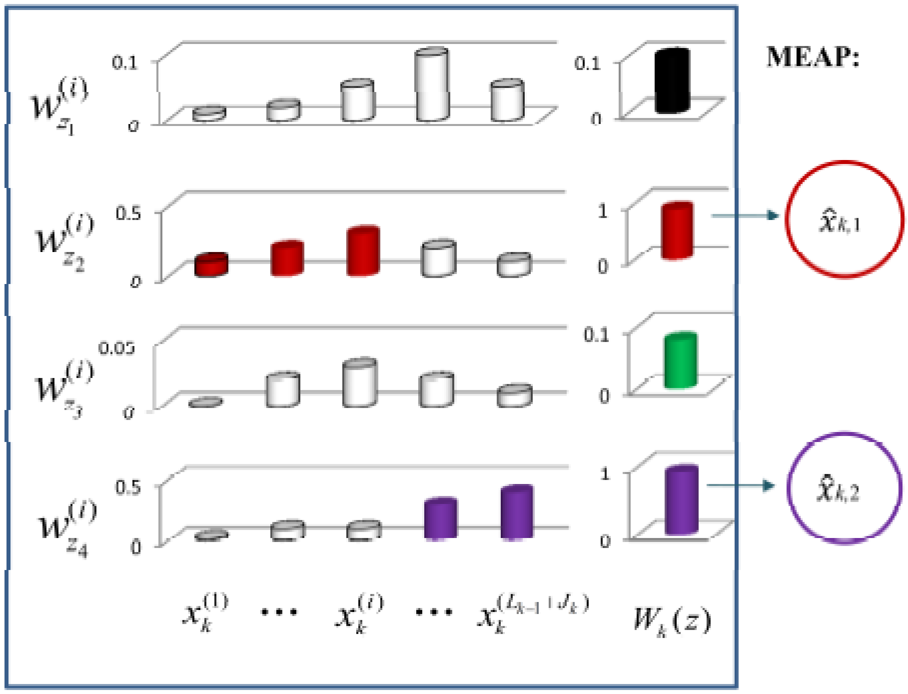

Figure 8: Illustration of the Multi-EAP estimator

Chapter 6

Results and Discussion

Result of Gauss-Newton Localization:

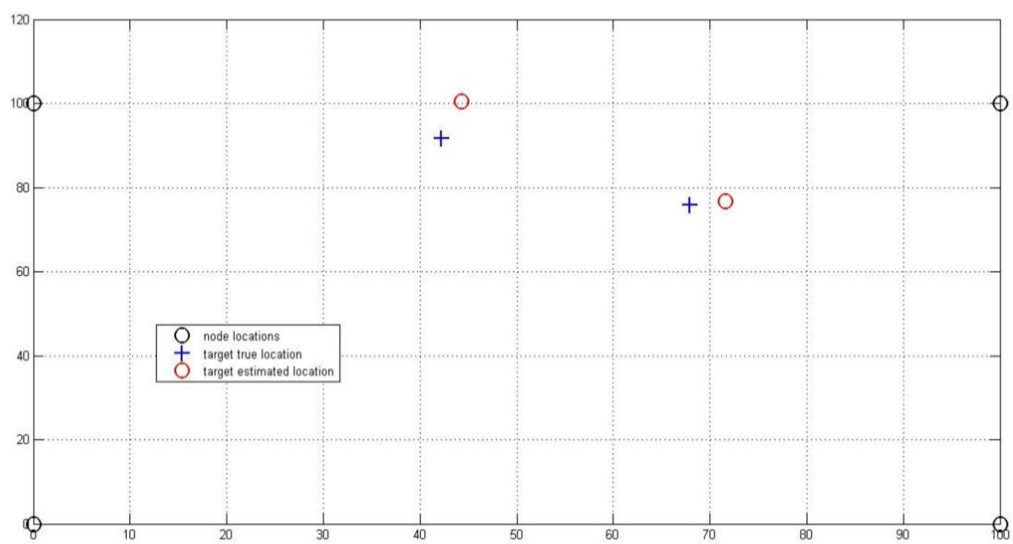

Figure 9: Illustrating the result of Gauss-Newton Localization method

Result of temporal ratio based localization technique:

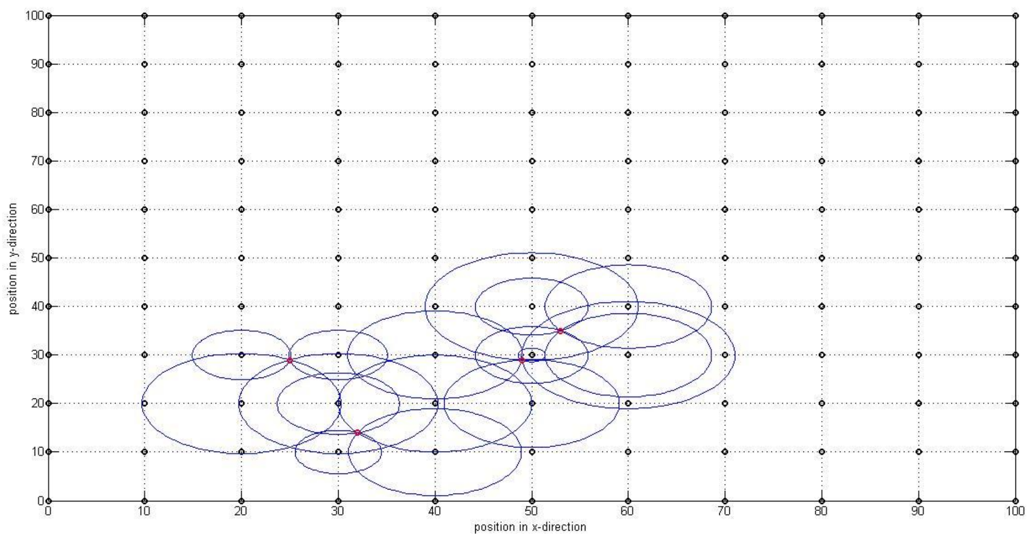

Figure 10: Tracking of target along with temporal ratio based localization technique.

Result of energy based collaborative target localization:

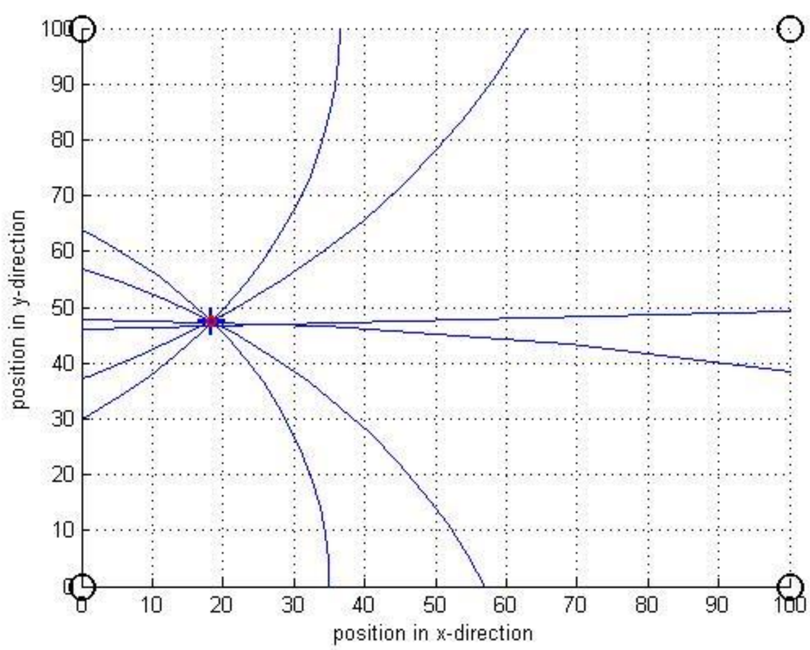

Figure 11: Result of Localization without transmitting power.

Result of tracking target using Gauss-newton localization and multi-hop communication model:

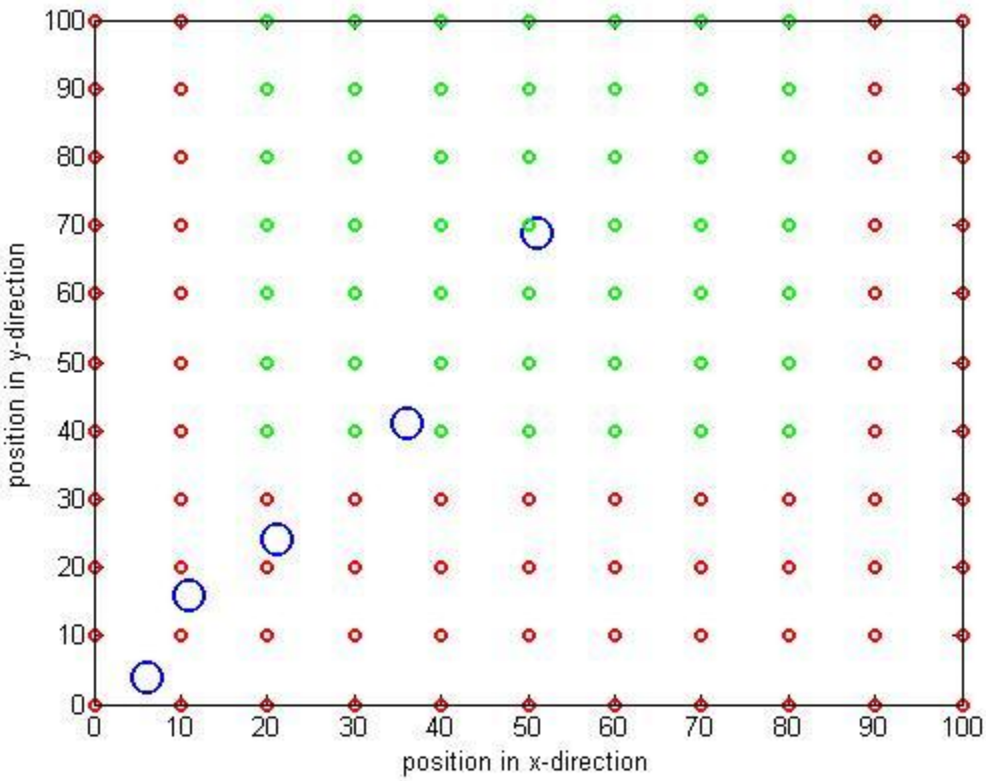

Figure 12: Gauss-Newton Localization Tracking in MHC

Determination of Direction of movement inside a cell:

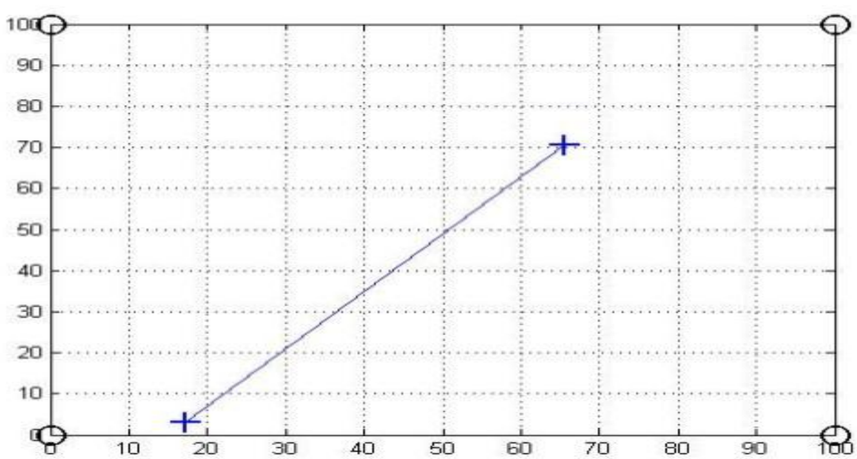

Figure 13: Direction measurement inside a cell,(225-315)

Result illustrating the two-tier multi-hop communication model:

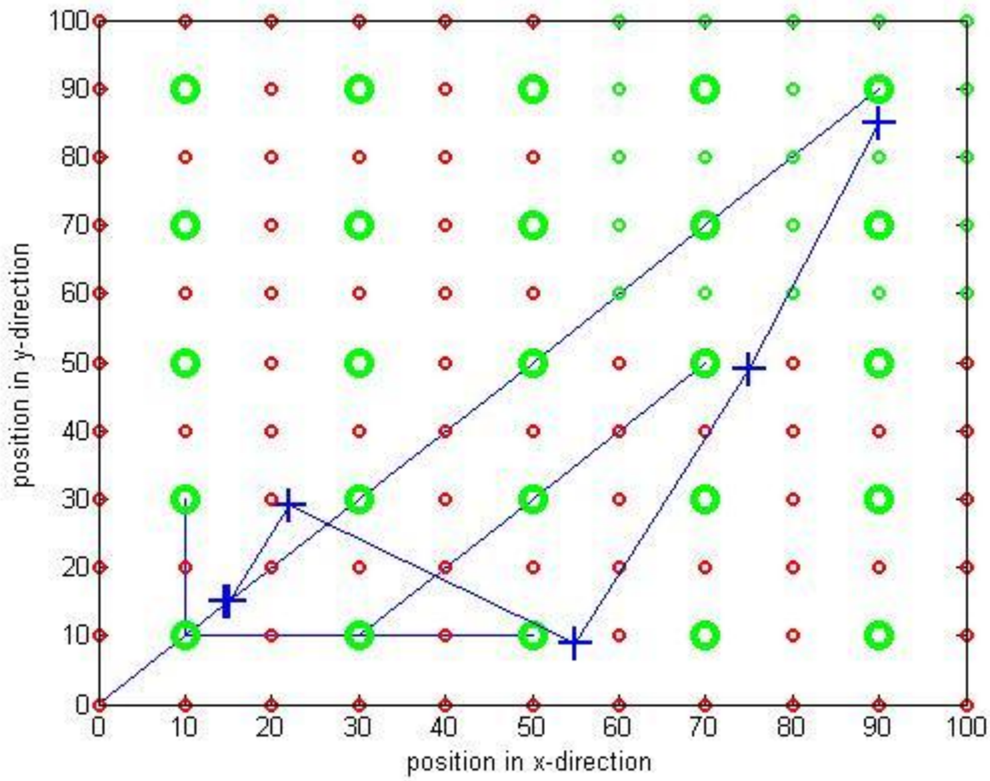

Figure 14: Efficient two-tier Multi-hop Communication network.

Multi-target tracking in polar co-ordinate system [7]:

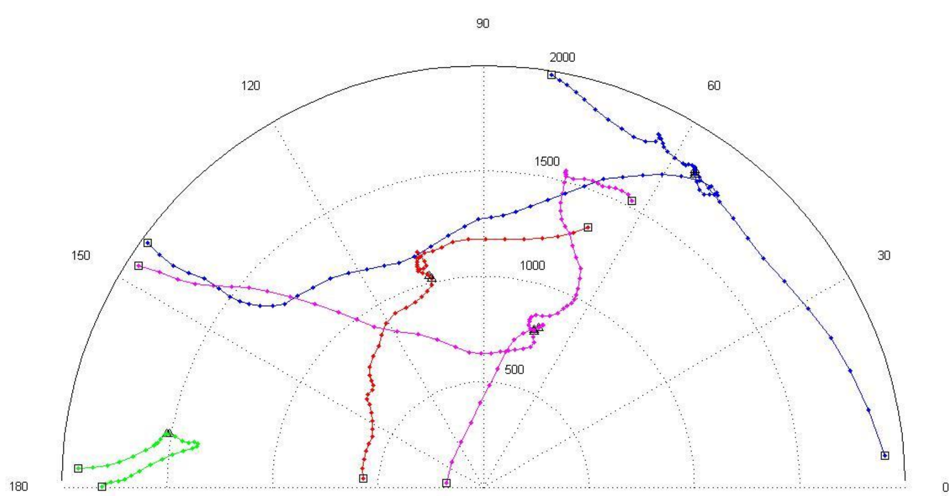

Figure 15:Multi Target Tracking in polar co-ordinate system

Observations of both Distance and Bearing (angle) [7]:

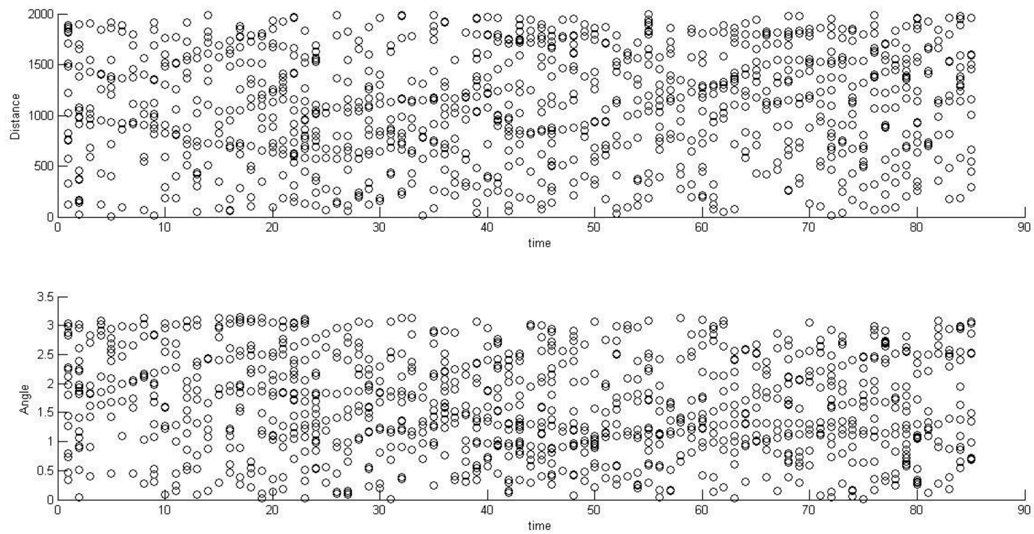

Figure 16: Observations of both Distance and Bearing(angle)

Comparison of different Multi-Estimate Extraction methods [7]:

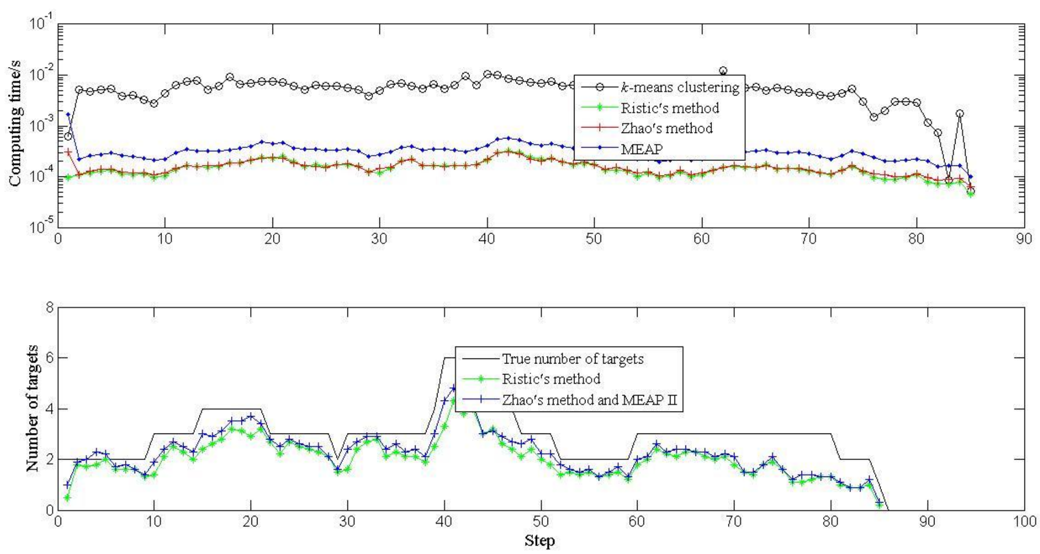

Figure 17: Comparison of different Multi-Estimate Extraction methods:

Discussion:

With the approach of sensor networks, the MTT issue moves from a brought together undertaking performed on a modest bunch of radar tracking stations to an omnipresent capacity in networks of a great many reasonable sensor nodes. In these frameworks, asset administration is significantly more discriminating than in conventional tracking frameworks because of the constrained bandwidth of the shared remote channel, the constrained accessibility of battery vitality or sun based force, and the restricted computational abilities of sensor nodes. This article has exhibited an end-to-end instructional exercise of how numerous target tracking can be executed for an asset constrained appropriated sensor network stage. By selecting a suitable combination instrument, sensor utility metric and a sensor tasking methodology, one can deliver a framework which productively tracks targets as free substances while they are broadly isolated. By including calculations for tracking in the joint space for targets in close vicinity to one another and a character administration plan to handle potential perplexities between intersection targets, we need think about just as a little number of targets at a time, staying away from the exponential intricacy when conceivable.

In adjusting the MTT ideal model for sensor networks, the centrality of sensor administration has get to be clear. Specialists need to start considering the bigger issue of asset administration. Assets incorporate sensor assets, network assets, computational assets furthermore, vitality/power assets. What is basic to see here is that these assets can be exchanged off between classifications. Case in point, one may substitute a bank of altered cameras for a container tilt unit. In the event that tracking is performed provincially, at that point nearby handling can be apportioned to perform tracking for a specific course a virtual container tilt. So also, if tracking is performed off board, a unit of network bandwidth spent in transporting information from an extra camera is identical to another virtual container tilt. Previously, these tradeoffs have been typical in equipment and framework plan, however in an asset oversaw framework, they may be differed progressively as per the framework's current abilities and prerequisites. As sensor networks move far from tracking tanks in the abandon and boats adrift, and into swarmed human situations, customary different target tracking methodologies will hit their cutoff points. These frameworks will need to know their energy, reckoning and correspondence cutoff points, center their detecting assets, and part their induction assignments suitably. This is the manner by which they can tame an intricate world.

Chapter 7

Conclusions and Future scope

A multi-EAP (MEAP) estimator is proposed to concentrate state-evaluation of various targets for the SMC-PHD channel by planning the issue roughly as a group of parallel sub-issues; each is a solitary observation single target state-estimation that is tackled by utilizing the ideal EAP estimator. The proposed methodology is free of iterative grouping reckoning and yields exact and solid estimation, which is direct to be utilized in propelled forms of the SMC-PHD channel. It is moreover suitable for parallel handling. Reproductions have shown its conspicuous prevalence over cutting edge strategies as far as both figuring rate and estimation exactness. The benefit of MEAP is accentuated when the targets are well inaccessible and when the disarray rate is low. By and large, MEAP is qualified to serve as one of the standard MEE answer for the SMC-PHD channel. Two testing circumstances stay open issues for dependable and precise MEE for the SMC-PHD channel. One is to recognize mess that is produced nearly to genuine targets in order to go around overestimation of the PHD as well as the bogus estimation of targets. The other is to gauge the condition of miss-identified targets that may be numerous in one output. For these two issues, restricted data of one single casing just is not any more sufficient. In our perspective, one needs to endeavor various casing data on the other hand even amplified data of targets (e.g. the shape, the shading, and so on.). Future scope of this project incorporate taking care of the MEE with "track coherence" and the RFS-based Bayes smoother to enhance the incorporated yield for the tracker.

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